

**USING A HANDS-ON ROBOTICS PROJECT TO AFFECT SKILL
DEVELOPMENT IN A CONTROL ANALYSIS COURSE**

A Thesis
Presented to
The Academic Faculty

by

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In Partial Fulfillment
of the Requirements for the Degree
Master of Science in the
Daniel Guggenheim School of Aerospace Engineering

Georgia Institute of Technology

May 2021

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USING A HANDS-ON ROBOTICS PROJECT TO AFFECT SKILL DEVELOPMENT IN A CONTROL ANALYSIS COURSE

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Date Approved: April 29, 2021

ACKNOWLEDGEMENTS

Firstly, I would like to thank my parents, Leonardo and Solange Inghilleri, for their undying love and support. I regularly call upon them for encouragement, counsel, and nourishment. My father's attention to detail, mastery of language, and encyclopedic knowledge seems greater than any modern internet search could provide. My mother's willingness, consideration, and lovingly cooked meals provided critical support, mentally and physically. I could not have made it this far without them. Thank you and I love you.

A great thank you to my thesis committee, Dr. Karen Feigh, Dr. Joseph Oefelein, and Dr. Kelly Griendling. While each of you played a critical role in the completion of this work, you also contributed greatly to my growth as a student and an engineer. Dr. Griendling, your devotion to my deadlines was the structured medicine I needed. If it were not for the cracking of your whip, I would still be staring at a blank page wondering how I was going to start. I am grateful you held my feet to the fire, thank you. Dr. Oefelein, I am grateful for your objective point of view, your tolerance of my mistakes, and your willingness to help me find reconciliation when I fell short. Dr. Feigh, your thorough feedback on my metric design allowed me to create a final product of which I am proud to present. Thank you for your support.

Lee Kanna, thank you for your vast technical experience, unending willingness to listen, and refusal to hold your punches. I needed your help, even when I did not like the delivery. I feel lucky to have shared a workspace with a truly outside-the-box thinker. Thank you to the T3 team: Mariah Brandon for your immensely coordinated kit deliveries, product support and soldering wizardry; Joel Dunham for your exactness and guru-like control theory expertise; Marine Leabeater for your vast expertise on the science of learning. I wish the three of you the best of luck

on your future endeavors. Dr. Merrick Furst, Leon Price, Mary Realff, and the rest of the Center for Deliberate Innovation, thank you for revealing the biases that underlay our decisions, what you showed me feels like donning a new pair of glasses. Thank you, Chris Lundy, for compiling much of our academic data. I also want to recognize the immense support the TRECS teaching assistants provided with implementation and device support; AJ Wilson, Carly Wood, Nick Liccini, Joshua Frial, & Nathan Cissell.

To all my friends who weighed in on this work and those who did what they could to take my mind off it, I love you all and am so grateful to be surrounded by such high caliber people. I wish I could name every single one of you, but I am sure I will leave out many influential people. To my aerospace colleagues, Sam Kemp, Allen Boehmig, Michael Castelein, John Cavender, Arega Margousian, Akash Patel, and Vijay Narayanan, I feel like I have stood among giants of intellect and compassion. To the Bicycle Doctor crew, Joel Rapkin, Max Rapkin, Dr. Fikret Atalay, Scott Mosko, and Yousef El-Shaer, you kept me grounded and laughing, which I desperately needed. Lastly to my dear friends, Wesley Rimmer, Patrick McGinty, Austin Tillison, Katlyn CoFrancisco, Jake Wooldridge, Ben Ruther, and Darin Czech, I am so grateful for your support and what seems like your endless ability to listen to my ramblings.

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LIST OF SYMBOLS AND ABBREVIATIONS

CIOS	COURSE INSTRUCTOR OPINION SURVEY
DCPS	DIRECT CURRENT POWER SUPPLY
ESC	ELECTRONIC SPEED CONTROLLER
KIPPAS	LABORATORY LEARNING METRICS
LQR	LINEAR QUADRATIC REGULATOR
MC	MICROCONTROLLER
N_A	NONUSER GROUP AFTER COURSE (POST-SURVEY RESPONSES)
N_B	NONUSER GROUP BEFORE COURSE (PRE-SURVEY RESPONSES)
OPT.	OPTIMAL CONTROL
PCB	PRINTED CIRCUIT BOARD
PID	PROPORTIONAL INTEGRAL DERIVATIVE (CONTROL)
SS	STATE SPACE REPRESENTATION
TF	TRANSFER FUNCTIONS
TRECS	TRANSPORTABLE ROTORCRAFT ELECTRONIC CONTROL SYSTEM
U_A	USER GROUP AFTER COURSE (POST-SURVEY RESPONSES)
U_B	USER GROUP BEFORE COURSE (PRE-SURVEY RESPONSES)

SUMMARY

This study aims to assess the impact on skill development of a hands-on experimentation and learning device within the undergraduate aerospace control analysis curriculum at Georgia Institute of Technology. The Transportable Rotorcraft Electronics Control System (TRECS) take-home lab kit was used as a hands-on learning treatment on 37.5% ($n=24$) of the Fall 2020 Control Analysis course taught by Dr. Chance McColl. The other students ($n=40$) in the course were taken as a control group. A Likert scale skill evaluation survey was performed to determine which skills are developed while using the TRECS. The response distributions and an accompanying Mann Whitney U-test can be found in the results section. On the topic of optimal control algorithms, which are extensively covered in the course lecture material and applied in the TRECS project, Users and Nonusers reported significantly ($p=0.10$) increased response and Users were found to have significantly ($p=0.10$) improved beyond Nonusers. Response distributions for topics including PID control, embedded software, and other electronics were not found to change significantly throughout the course, despite the application of the TRECS treatment or the presence of the topic in the course curriculum. The other goal of this research was to propose an improved study which addresses the limitations to this dataset such as small sample sizes, self-reports, sole focus on development of course-specific subject matter and selection bias from the lack of random assignment of the treatment. The recommendations for a future study are aimed to improve trustworthiness, increase transferability, and incorporate multiple verification elements including the development of a new skill assessment that could evaluate students' application-level understanding of course concepts.

CHAPTER 1. INTRODUCTION AND BACKGROUND

In the early 1980's, as educational strategies and teaching styles began to incorporate the works of psychologists and philosophers, the engineering education pendulum began to swing back from the theoretical and towards the practical [1, 2]. New teaching and learning styles were developed that viewed the educational experience as a holistic one, requiring the inclusion of experience, perception, cognition, and behavior. In 1984, David A. Kolb published *Experiential Learning* [3], a unification of the contributions and insights of scholars such as William James [4], John Dewey [5], Kurt Lewin [6], Jean Piaget [7], Lev Vygotsky [8], Carl Jung [9], Mary Parker Follett [10], and Paulo Freire [11]. In this book, Kolb presents his Experiential Learning Theory (ELT) as a dynamic, holistic theory of the process of learning from experience and a multi-dimensional model of adult development. The theory establishes a four-stage learning cycle: concrete learning, reflective observation, abstract conceptualization, and active experimentation. Kolb's ELT became the cornerstone for decades of research and demonstration of experiential learning in the universities.

Dr. Richard M. Felder, another pioneer in this field, picked up Kolb's ELT and applied it directly to engineering education. In 1988, Dr. Richard M. Felder and Dr. Linda K Silverman published *Learning and Teaching Styles in Engineering Education* [12], a breakthrough paper that introduced insights and psychological expertise to the teaching styles of engineering in universities. Felder *et al.* effectively started an entire branch of learning research known as engineering education. He later would articulate inductive and active teaching learning methods that become the backbone for project-based learning and capstone design courses across the institutional landscape [13, 14]. Swaths of papers were written on the topic of active learning which

eventually caused the definition of active learning to become ambiguous [15]. The term became a buzzword and began to separate itself from the framework originally proposed by Felder, which in part is defined as student-centered approach that facilitates the construction of knowledge with meaningful hands-on learning activities.

Although much emphasis has been placed on hands-on and active learning strategies, these are not the “silver-bullet” solution to education. Many of the psychological foundations of active learning theories are derived from the behavior of children like Piaget’s constructivism [7] or Vygotsky’s proximal zone of development [8]. It should be obvious that the learning processes of students in modern universities are more complicated [16]. There may seem to be mounting evidence against classical lecturing techniques, but there are many reasons to hold on to this ancient teaching style, particularly in the math and sciences. Lectures are particularly effective of transmitting conceptual knowledge as they provide an opportunity for concepts to be laid out, explained and expounded. Often, this allows students to learn to the arithmetic necessary for demonstrating math and science theorems. [17] Indeed, cognitive scientists like Steven Pinker [18] have argued that basic knowledge, not only in math but in many fields of science, cannot really be learned without a substantial amount of direct exposition. Charlton *et al.* [19] posits that lecturing exploits the spontaneous human aptitude for learning from spoken (rather than written) information. Literacy is a recent cultural artefact, and for most of their evolutionary history humans communicated by direct speech. By contrast with speech, all communication technologies – whether reading a book or a computer monitor – are artificial and unnatural. Furthermore, students are not always the reliable, self-motivated pillars of educational engagement that active learning methods require them to be, and thus, an instructor-centered learning environment provides structure and motivation that may otherwise be lacking. A balance between lecturing and hands-

on activities may allow educators to reap the benefits of both styles of teaching and learning. Brereton *et al.* [20] demonstrated that engineering students learn and develop engineering fundamentals by continually translating between hardware (active learning experiences) and abstract representation (conceptual lecture material.) Thus, this study aims to observe the implementation of hardware alongside a traditional lecture-based engineering course with the intent of measuring whether the hardware experiences can deepen the level of conceptual understanding of course-specific subject matter.

1.1 Active Learning Via Hardware

The primary mechanism for active and experiential learning experiences in engineering education occurs is the laboratory course. A series of fundamental objectives for engineering instructional laboratories was set forth by Dr. Lyle D. Feisel and Dr. Albert J. Rosa in 2005 [21] and has since been widely accepted as an excellent framework. In order to measure the efficacy of laboratory learning outcomes, Brinson *et al.* [22] developed the standardized metric, KIPPAS, designed to address the National Research Council's goals of laboratory experiences [23, 24]. Additionally, Dr. Mahmoud Abdulwahed [25] at the Engineering Center of Excellence in Teaching and Learning set forth a model for laboratory learning that directly incorporates Kolb's Experiential Learning Theory. The method implements a combination of remote, virtual, and hands-on laboratory sessions. As technology has rapidly developed, educational laboratory set-ups have changed and utilize more remote, virtual, and take-home experimentation.

There is still deliberation over the value of hands-on versus simulated laboratories, a debate further confounded by researchers' use of varying educational metrics as criteria for judging the laboratories. Advocates of hands-on learning emphasize the development of design skills [26, 27]

while remote lab advocates focus on conceptual understanding [28]. Brinson *et al.* [22] showed that in 89% of comparisons between traditional in-person labs and non-traditional virtual/remote labs, virtual/remote labs had equal or higher learning outcomes. Of course, the degree of difference in achievement is dependent upon the outcome measured and Brinson *et al.* concluded that studies supporting higher achievement in non-traditional labs place emphasis on content knowledge and understanding whereas studies supporting traditional labs rely heavily upon qualitative data related to student and/or instructor perception [22]. This review did not cover take-home lab kits, which are both physical in-person experiences, and non-traditional laboratories as they can be performed from anywhere, including outside the classroom. For many engineering disciplines, these take-home lab kits come in the form of robotics activities.

There have been many recent efforts to implement hardware-based experimentation into engineering courses. These hands-on learning efforts have been applied to a multitude of engineering disciplines. Low-cost portable hardware platforms are the subject of this study; thus, it is important to situate our work in the context of the broader literature. In general, studies on the efficacy of educational robotics and robotic hands-on activities are plentiful. In K-12 STEM education, the use of educational robots to enhance students' interest, engagement and academic achievement is steadily increasing [29-31]. Positive outcomes for the general effectiveness of educational robotics include students' learning and transfer of skills, improved creativity and motivation, broadening and diversifying participation, and teachers' professional development. However, not all implementations of educational robots are created equal; thus, some studies have found no improvement in learning outcomes [29, 30]. Similar broad reviews on the effects of individual experimental hardware at the university level are difficult to find, as the breadth of subject matter grows immensely in higher education programs, possibly because it is difficult to

show transferability for specific implementations of educational robotics. Nevertheless, detailed implantations of hands-on learning devices in engineering education are plentiful; some examples of which follow.

B. Taylor *et al.* [32] designed a three degree of freedom helicopter system with which students could individually perform experiments at home. The helicopter is interfaced with a National Instruments myDAQ data acquisition module. The complete system provided the students with a rich and challenging control problem. Taylor found that almost all the students who used the hardware enjoyed the course and would actively recommend it to future students. Although this system is a well-designed experimental hardware platform, demonstration of its specific efficacy as a learning tool was not found.

H. Li *et al.* [33] applied experiential learning theory to redesign a mechanical engineering course with the intent of increasing student engagement and improving learning outcomes by implementing a course-long hardware-based project and aligning the lecture material with the development of the project. This approach allowed students to directly apply what they were learning in the classroom to a physical gearbox model. Often referred to as Kolb's model of experiential learning, students iterated through a "Do, Observe, Think, Plan" cycle. The course also emphasized having group discussions, raising questions, and getting feedback. According to university wide instruments for collecting student feedback, the percentage of students who were satisfied with the course improved from 26.5% to 67.7% and the percentage of students who agreed that the teaching on this course was effective in helping them learn grew from 29.4% to 71%.

Another application of Kolb's experiential learning model was undertaken by a research team at the National University of Singapore [34], where a second year chemical engineering course,

notorious for its theoretical intensity and difficulty, was redesigned to include several parallel hands-on activities that concluded with a design project. The activities comprised of designing and performing experiments that were relevant to the final design project. Throughout the course, the lecture material was aligned with the hands-on activities to provide theoretical support and develop conceptual understanding. Positive feedback was received from the students, particularly about the hands-on learning activities, but no effort was made to compare learning outcomes with a control group of students who did not perform the activities or to assess the skills of these students before and after the course.

A better approach to evaluating efficacy of these hands-on experiential learning activities would be to compare students who performed the activity with students who did not. At the University Kebangsaan in Malaysia, an experiential robotics project was implemented in an undergraduate engineering course [35]. The students were separated into two groups, experimental and control. The experimental group underwent a revised course, based on Kolb's ELT, that aligned lecture material with a robotics programming project while the control group underwent the traditional lecture-based approach. The metric for evaluation was a comparison between marks received on a midterm exam before the project and a final exam after the project. The researchers found that project users scored higher marks on the final exam when compared to nonusers and to users' prior midterm exam. The final exam included questions related to the application of programming in the real world and thus the experimental group had an obvious advantage.

Due to their potential to limit bias, randomized control trials (RCT) are highly valued as evidence to determine whether a treatment is effective. Handley *et al.* [36] explain that random allocation minimizes selection bias and maximizes the likelihood that measured and unmeasured confounding variables are distributed equally, enabling any differences in outcomes between the

intervention and control arms to be attributed to the intervention under study. One RCT study [37] compared process and learning outcomes between remote, hands-on, and simulated lab environments. Here, Corter *et al.* controlled for instructor variation by randomly assigning experimental conditions to lab sections and instructors. The researchers used post-lab knowledge tests, as well as an assortment of qualitative ratings (learning effectiveness, satisfaction, immersion, etc.) to assess the superiority of the three lab environments. The hands-on lab provided the greatest learning outcomes when students worked in a group and the remote lab had the highest learning outcomes when students were working individually. There was some disagreement between the knowledge tests and the students' ratings of learning effectiveness, such that students rated the simulated lab as most effective, despite the knowledge tests scores of that group being the lowest.

In another example of RCT, DeBoer *et al.* [38] estimated the impact of at-home lab kits on a large online course known as a Massive Open Online Course (MOOC.) This study aimed to support the MOOC by investigating whether an at-home electronics hardware lab-kit could affect learning outcomes as well as attitudinal student variables such as self-efficacy and self-concept as a scientist. The lab-kit was randomly assigned to the experimental group (n=185), distinguishing them from the control population (n=~5000.) The study used the Motivated Strategies for Learning Questionnaire (MSLQ) [39] to retrieve qualitative findings and the final exam grades for the knowledge assessment. The MSLQ was sent before and after the lab-kit project. The experimental group scored higher on average. Self-efficacy, a measure of students' confidence in their understanding and ability to conceptualize the course material, was found to be greater in the experimental group. The limitations of this study include that the MOOC suffers from very high dropout rates, greater than 80%, thus the sample size of the experimental group was reduced to

just 34 students. This may have impacted the results as the measurements of learning outcomes and confidence were only taken from students who completed the course, leaving out most of the students' who interacted with the hardware. Thus, the sample taken from the population of students who completed the course is not be representative of the total population of students who interacted with the hardware. Hence, the true effect of the hardware implementation is difficult to ascertain.

1.2 Thesis Contribution

This thesis explores a case study illustrating the potential impacts of manipulatives in a junior level control analysis engineering course in the Daniel Guggenheim School of Aerospace Engineering at the Georgia Institute of Technology. Students participated by engaging individually with a hands-on learning robotics project that allowed for experimentation and application of the course curriculum. Some of the findings of this study are constrained by its specificity, however, some overarching patterns may suggest transferability.

Specifically, this research explored the ability of active learning to improve practical skill development and conceptual understanding in engineering controls analysis using an implementation of the Transportable Rotorcraft Electronic Control System (TRECS). The control analysis curriculum was chosen because it is bimodal, such that it is simultaneously universally practical and theoretically mathematically vigorous. In addition, many educational robotics have been developed for it, and thus the efficacy of the TRECS may be transferrable to other devices. These devices are inexpensive laboratory-quality physical systems that provide students with active, hands-on learning experiences and an experimental environment to connect theoretical course concepts to practical applied experiences. These active learning experiences have the

potential to deepen application-level understanding and increase student engagement in curriculum.

Another goal of this thesis is to use the results from this study to suggest a framework for future studies on this and similar concepts. A broader study was designed to evaluate transferrable qualitative findings as well as generalizable quantitative results. The new study addresses the measurement of analytical skills, which are minimally represented in previous research [22], as well as knowledge & understanding of course content and practical skills.

CHAPTER 2. RESEARCH METHODOLOGY

2.1 Description of TRECS

In the Spring of 2018, a novel hands-on learning project was deployed in an undergraduate control analysis and design course in the Daniel Guggenheim School of Aerospace Engineering at Georgia Institute of Technology. The project, known as the Transportable Rotorcraft Electronic Control System (TRECS), incorporates individual hardware experimentation, links to theoretical course content, and a low-cost barrier to ensure student participation. With all the requirements met, the TRECS is one example of an educational robot that when deployed could increase the amount of active learning experiences students have in the control analysis curriculum.

The Transportable Rotorcraft Electronic Control System (TRECS) is an active learning project developed for an undergraduate control analysis and design class as a 1 degree of freedom (1 DOF) arm with a motor and propeller.

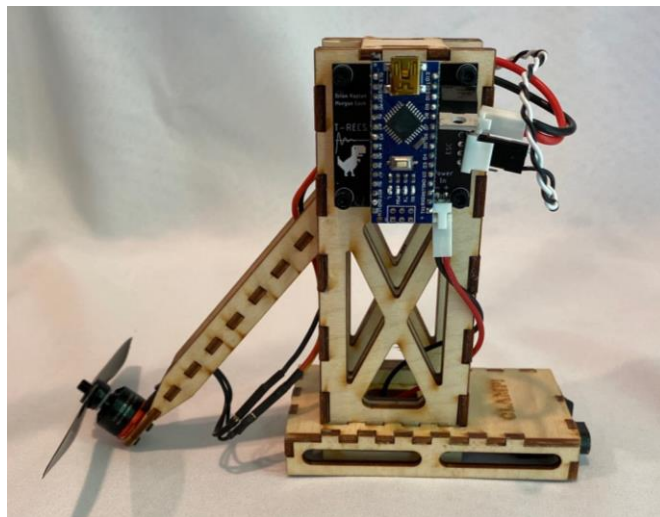


Figure 1 – The TRECS device, designed by Tangibles That Teach.

The system allows students to practice designing a control system that adjusts the speed of the motor to hold the arm at a preset angle. The complexity of the project can increase as professors see fit for the course. For example, the kits can be used to identify the dynamics of a simple mechanical system. A broad range of control algorithms can be designed and implemented ranging from PID to feedback linearization to optimal control via a linear quadratic regulator. In this studies implementation of the TRECS, student learning goals included:

- Assemble a robotic device that includes an Arduino nano, electronic speed controller, brushless DC motor, and rotary position sensor.
- Write sketches in the Arduino IDE that compile onto the system controller and allow for real-time visualization of sensor data using SerialPlot.
- Design, implement, and tune P, PD, and PID controllers on a physical 1 DOF system.
- Design, implement and tune an LQR controller that achieves pitch response requirements.
- Determine accurate estimations of physical parameters, unique to each device, that influence the dynamical response of the system.

The TRECS' printed circuit board comes soldered to an Arduino Nano with labeled ports for the power supply and the electronic speed controller. The structural components are precut and must be glued together by the student. The project is designed to be used individually and is compatible with any computer running Windows or MacOS. During the extent of the assignment, students have access to two undergraduate teaching assistants who were previous users of the TRECS and trained on implementation and troubleshooting.

There are three parts to the assignment: (1) device assembly & testing, (2) modeling & simulation, and (3) writing the final report.

2.1.1 Device Assembly and Testing

Part 1 includes ensuring the device is properly assembled and checking for successful operation by a running series of test codes provided to the students. It begins with an overview of the components of the device shown in Figure 2.

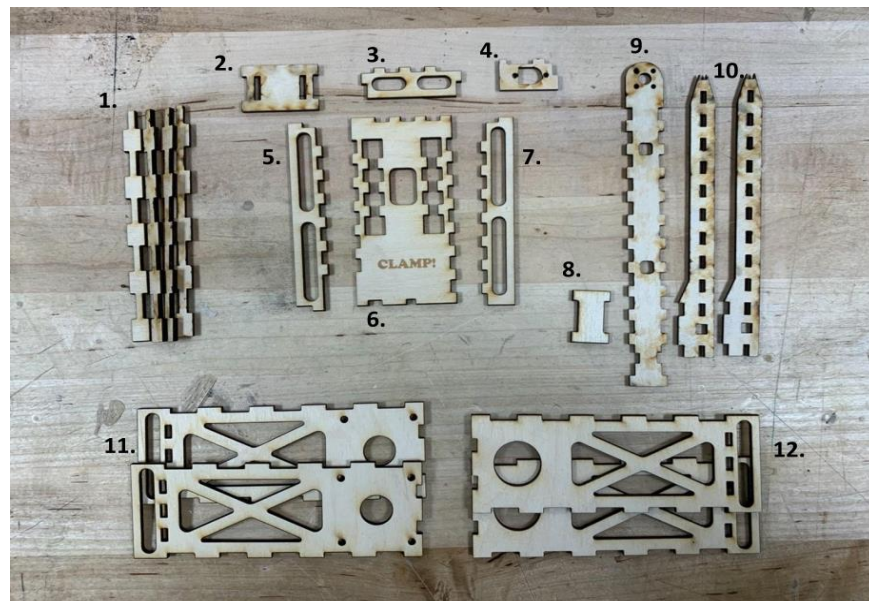
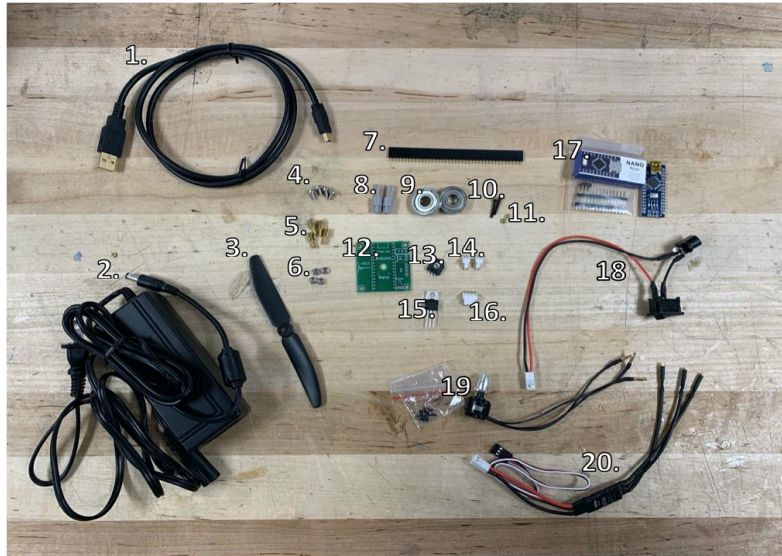


Figure 2 - TRECS structural parts overview.



Components Guide:

- | | |
|---------------------------------|-------------------------------|
| 1. 1x Programming USB cable | 11. 2x M2 nuts |
| 2. 1x Wall adapter power supply | 12. 1x T-RECS PCB |
| 3. 1x Propeller | 13. 1x Rotary position sensor |
| 4. 4x M3 screws | 14. 2x 2-pin receptacle |
| 5. 4x M3 standoffs | 15. 1x MOSFET |
| 6. 4x M3 nuts | 16. 1x 4-pin receptacle |
| 7. 1x 40 pin female connectors | 17. 1x Arduino Nano |
| 8. 2x shaft bearing inserts | 18. 1x Power harness |
| 9. 2x ball bearings | 19. 1x 1306 brushless motor |
| 10. 2x M2 screws | 20. 1x ESC |

Figure 3 - Overview of TRECS electronics and components

A step-by-step assembly instruction manual is provided to the students. Assembly requires only the use of basic tools and supplies such as hex keys, wood glue and sandpaper. The general process is assembling the structural base (Figure 4), then the swinging arm, then the vertical towers.



Figure 4 - Assembled base of the TRECS. The pieces interlock and glue together.



Figure 5 - Device arm with motor base, electronic speed controller and wiring installed.

The brushless motor and electronic speed controller are mounted onto the arm of the TRECS as shown in Figure 5. The Arduino mounts to the side of the vertical tower and the arm between the two towers. The bearings are installed in the tower to ensure the arm rotates smoothly, and the axle attached to the arm mounts onto a rotary position sensor for sensing the arm's angle. The fully assembled device is seen in Figure 1. After the assembly is finished, the device is ready to be tested to ensure proper functionality.

The first step to the device testing is to install the software development environment, Arduino Integrated Development Environment (IDE). This IDE allows users to interface with the Arduino Nano from their computers by writing scripts of code known as ‘sketches.’ The TRECS instruction manual provides a brief description of the basic operation of the IDE and its associated live feedback printer, the Serial Monitor. Similarly named, SerialPlot is a separate open-source program that is recommended to students for this project, as it allows for simple plotting and data logging, as well as live response plots for the TRECS. A brief description of the basic operation of SerialPlot is included in the TRECS manual. After the software is fully installed, four separate hardware performance tests are needed.

The first test is for the rotary position sensor. The students are provided with a sketch to upload to the Arduino IDE that verifies that the sensor is connected and operating correctly. As the sketch is running, changes in angle caused by moving the arm will display on the SerialPlot response plot. The second test is a data logging test to ensure that the response data is recording to a CSV file properly; this test also includes a check of pause/resume functionality. The next test calibrates the electronic speed controller using a provided sketch. During this test, students can experiment with open loop control of the motor by sending throttle values directly to the ESC via keyboard input. The last test is for the PID controller. The provided sketch allows students to input desired pitch angles while the motor is controlled by a PID algorithm to achieve the desired state. The students can check to ensure the proper operation of the PID controller and thus the testing and assembly of the TRECS is complete.

2.1.2 Modelling and Simulation

The students begin by deriving the dynamics of the system which are relatively straightforward. Figure 6 is a diagram is provided to the students in the project manual.

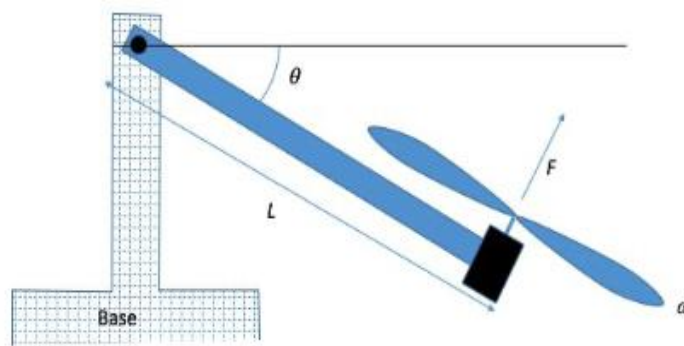


Figure 6 - Simplified dynamical model of the TRECS device.

The notation suggested is as follows:

- The mass of the motor is given by m .
- Moment of inertia of the system is given by J .
- The frictional coefficient on the lever arm is given by b .
- The thrust produced by the propeller is given by F , where ω is the angular velocity of the propeller and A is a proportional coefficient:

$$F = A\omega^2 \quad (1)$$

The assumptions are that ω is linearly proportional (by a factor of k) to the drive signal, u and that the lever arm's mass is negligible. The equation of motion can then be derived as the following:

$$\ddot{\theta} + \frac{b}{J}\dot{\theta} + \frac{mgL}{J}\cos(\theta) = \frac{Ak^2L}{J}u^2 \quad (2)$$

Or by replacing the constant coefficients with C_1 , C_2 , and C_3 respectively,

$$\ddot{\theta} + C_1\dot{\theta} + C_2\cos\theta = C_3u^2 \quad (3)$$

The next objective is to estimate the values of these coefficients by comparing a simulation of the system to the actual performance of the TRECS. Each system will have its own unique coefficients due to variability in construction. A drop test is the suggested method to solve for C_2 , where the arm of the device is held at $\theta(t_0) = 0^\circ$ and then dropped with zero initial velocity, $\dot{\theta}(t_0) = 0 \text{ rad/s}$, to its resting position around -45° .

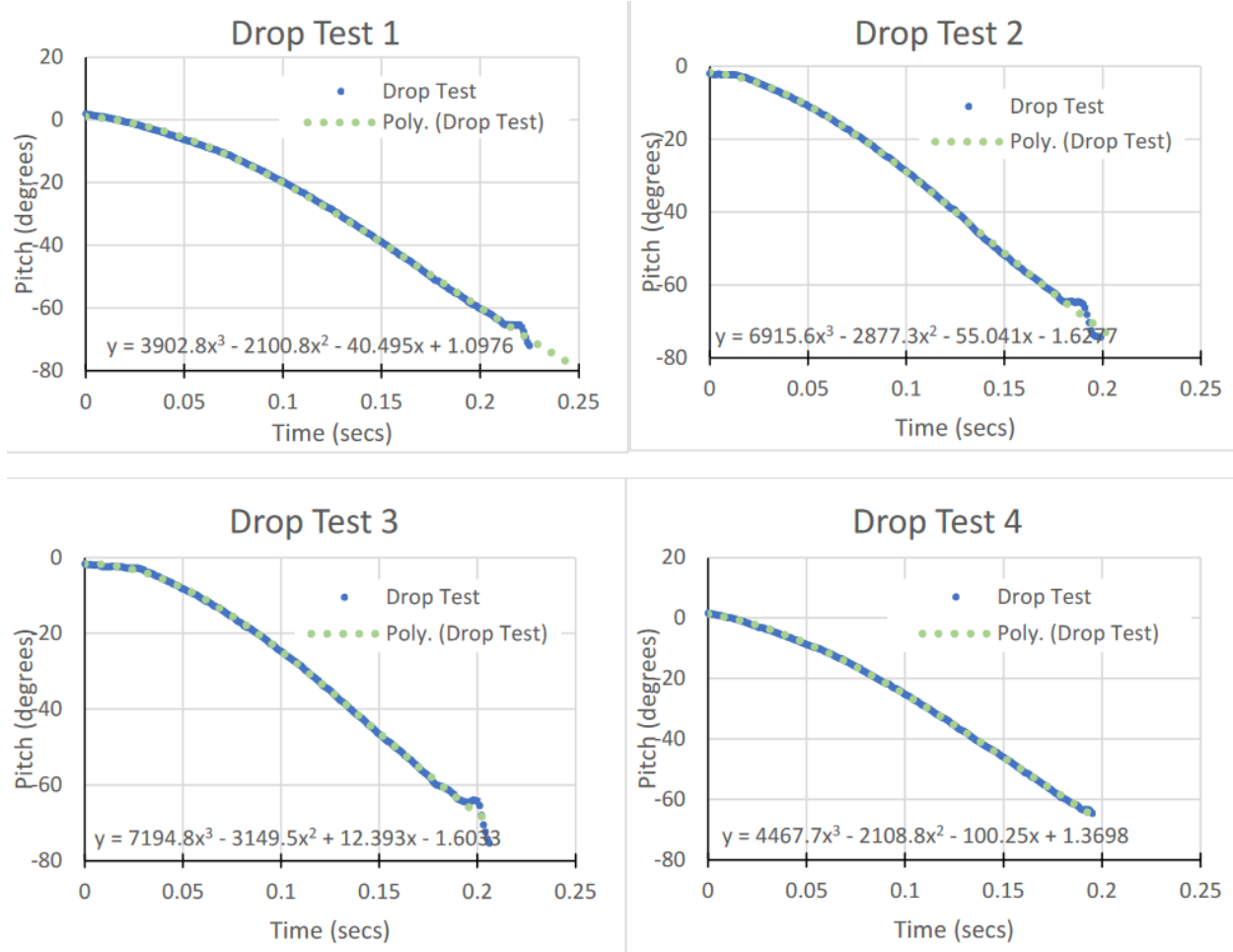


Figure 7 - Experimental drop test with 3rd order polynomial curve fitting [40].

A 3rd order polynomial curve fitting is applied to the angle response plot. Then the second derivative can be taken, and the resulting equation approximates $\ddot{\theta}(t)$. The initial conditions of $\theta(t_0) = 0^\circ$ and $\dot{\theta}(t_0) = 0 \text{ rad/s}$ and the second derivative of the polynomial approximation are substituted back into equation 3 and simplified to solve for C_2 . This process should be repeated several times to gather multiple estimates and then averaged to find the best estimate.

To calculate C_I , a hover test is performed where a constant input is sent to the motor to hover the arm in a steady state position. In this steady state, the dynamics are described as:

$$C_2 \cos \theta = C_3 u^2 \quad (4)$$

Using the C_2 value previously determined, it is simple to calculate a value for C_3 . Repeating the steady state test with a variety of input magnitudes will achieve a more accurate coefficient value. The last coefficient, C_1 can now be determined graphically by simulating the system by solving the dynamical equation. The assignment suggests using ODE45 in MATLAB to do this. By inputting an array of C_1 values, students can match the best model fit to the actual system response.

2.1.3 PID Controller Tuning, Testing and Analysis

Now that the device is assembled and calibrated and the system dynamics have been verified, the students begin to apply feedback control to the TRECS. This section of the assignment covers the bulk of the material that is required to be documented in the final report. The basic feedback control loop is shown in Figure 8.

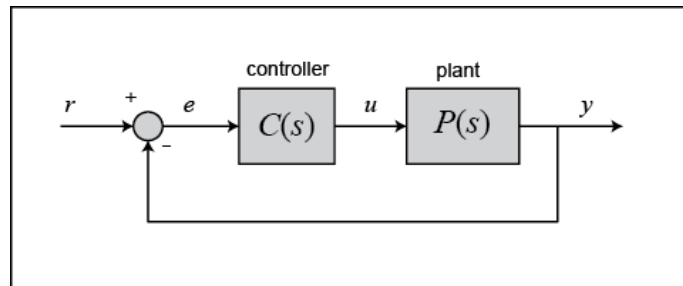


Figure 8 - Feedback control loop with controller and plant blocks.

Where the error term,

$$e(t) = r(t) - y(t) \quad (5)$$

Is in terms of the commanded signal, $r(t)$, and the output, $y(t)$. This error can be rewritten as,

$$e(t) = \theta_d(t) - \theta(t) \quad (6)$$

Such that $\theta_d(t)$ is the desired pitch angle. The students design a proportional (P-controller), proportional integral (PI-controller), and a proportional integral derivative (PID controller) and subject them to tuning and testing to achieve a series of requirements. The equations for these controllers are as follows:

$$P: u(t) = K_P(\theta_d(t) - \theta(t)) = K_P e(t) \quad (7)$$

$$PD: u(t) = K_P(\theta_d(t) - \theta(t)) + K_D(\dot{\theta}_d(t) - \dot{\theta}(t)) = K_P e(t) + K_D \frac{de(t)}{dt} \quad (8)$$

$$\begin{aligned} PID: u(t) &= K_P(\theta_d(t) - \theta(t)) + K_D(\dot{\theta}_d(t) - \dot{\theta}(t)) + K_I \int_0^t (\theta_d(t) - \theta(t)) \\ &= K_P e(t) + K_D \frac{de(t)}{dt} + K_I \int_0^t e(t) \end{aligned} \quad (9)$$

As the students tune the gain values for their controllers, they also compare the experimental responses to the simulated ones. Figure 9 shows how changing the gains affect the TRECS pitch response. As the students tune the gains for these controllers, a constant desired pitch angle is used. After they achieve adequate performance from the PID controller, the device is subjected to a more complex maneuver, a step change from a 0° hover to a 15° degree hover.

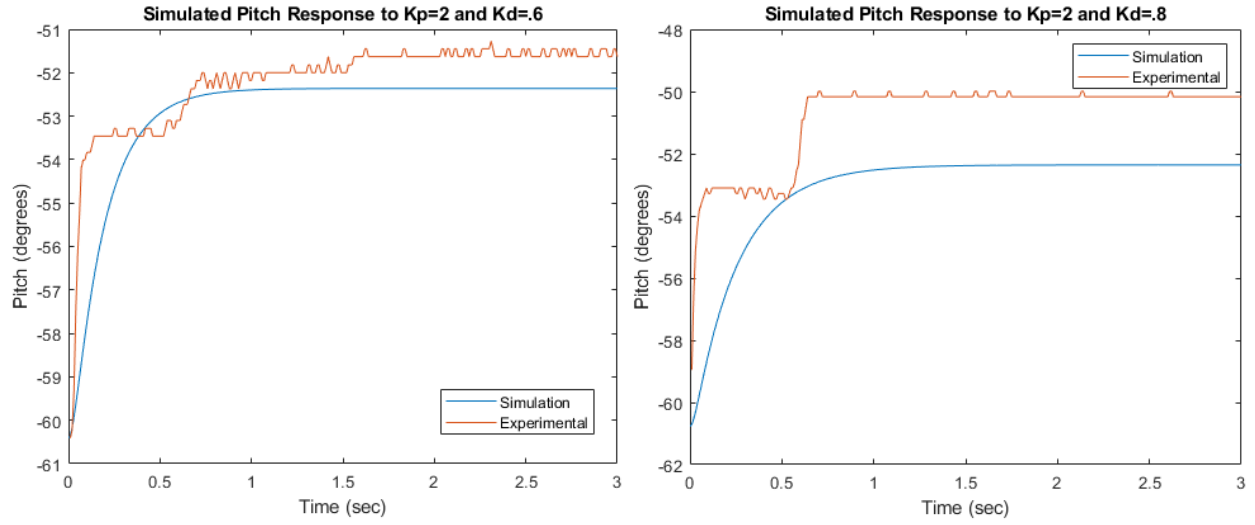


Figure 9 – Pitch angle response plots while gain tuning, PD controller on the TRECS [40].

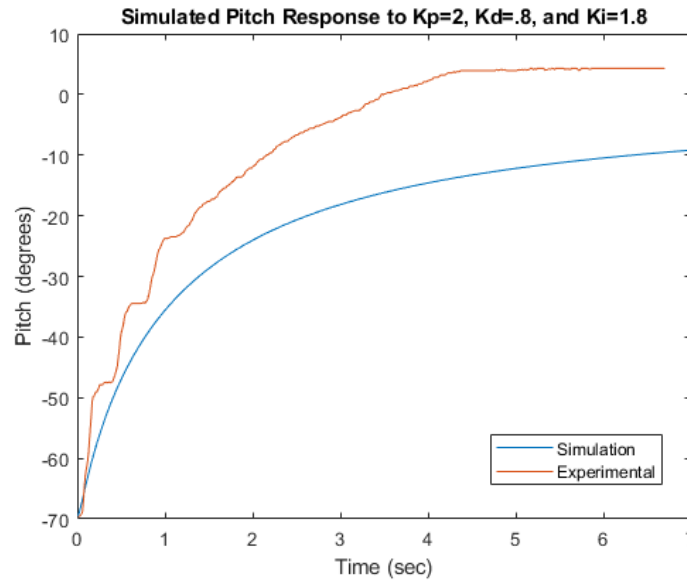


Figure 10 - PID controlled TRECS pitch angle response [40].

2.1.4 Optimal Control Using LQR

The last part of the control design uses a linear quadratic regulator (LQR) to determine optimal PID gain values. The students are initially tasked with optimization of the PD controller. This is performed by transforming the system into state space representation.

$$\begin{bmatrix} \dot{\theta} \\ \ddot{\theta} \end{bmatrix} = \begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & -C_1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} 0 \\ C_3 \end{bmatrix} u^2 \quad (10)$$

To solve a continuous time LQR problem, the full state-feedback law, $u = -Kx$, is used to solve the quadratic cost function, equation 11. The TRECS manual recommends using the MATLAB function, `lqr()`.

$$J(u) = \int_0^\infty (x^T Q x + u^T R u + x^T N u) dt \quad (11)$$

The function returns the solution, S , to the Riccati equation before deriving the gain matrix, K .

$$A^T S + S A - (S B + N) R^{-1} (B^T S + N^T) + Q = 0 \quad (12)$$

$$K = R^{-1} (B^T S + N^T) \quad (13)$$

The resulting K_P and K_D values are used in the LQR optimized PD controller. To find the optimal K_I a variation of this process is performed by adding a third state, thus increasing the dimensionality of the solution, K , to 3x3 and providing the third gain value. An optimized PID response is shown in Figure 11.

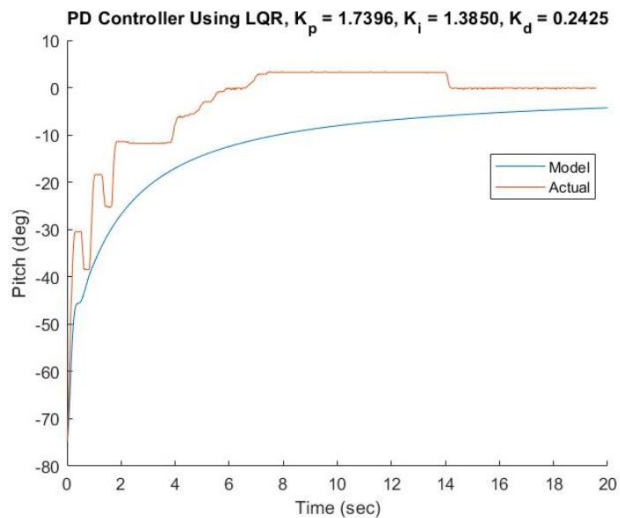


Figure 11 - LQR + I optimized PID controlled TRECS pitch angle response [41].

2.1.5 Final Report

Lastly, the final written report must include documentation of all the previous procedures as well as visualizations of the experimental data and comparisons with the simulation. A proper analysis must also be written which ensures students connect the theoretical course concepts to the practical application of the project. The report must be formatted according to a set of guidelines provided to the students. The grading rubric of the report can be found in the Appendix. The report forces students to connect theory from class to the overserved behavior of the real system, helping build connections as well as highlighting real-world challenges. Aligned with the KIPPAS laboratory learning outcomes [22], throughout the assignment, students sharpen their inquiry skills by making observations and creating and testing hypothesis of response behavior. The final report also demands that students utilize analytical skills to interpret data from the experiments. Students must compare the efficacy of various control algorithms and gain values by closely examining the

response plots and measuring response parameters. These free response questions draw upon a student's ability to critique, infer, predict, interpret, integrate, and recognize patterns in experimental data, and use this to generate models of understanding.

2.2 Course Description

The course selected for the deployment of the TRECS device was the 3rd year level Control Analysis and Design course of the Daniel Guggenheim School of Aerospace Engineering at Georgia Institute of Technology. The course covers wide range of topics, with each professor approaching it in a different manor. The Fall 2020 semester during which this study was performed was instructed by Dr. Chance McColl. The course topic outline is listed here in chronological order, including the timing of the TRECS assignment and the pre and post skill surveys:

1. **Introduction to Control Systems:** Examples of control systems, open loop vs. closed loop control, feedback block diagrams and their simplification, mathematical modeling of dynamical systems, modeling in the state space, transfer functions, and impulse response functions.
2. **Transient and steady-state response analysis:** First and second-order systems, higher-order systems, transient response analysis, time domain performance specifications, delay time, rise time, peak time, maximum overshoot, and settling time, stability analysis and Routh's stability criterion, proportional, derivative, and integral (PID) control actions, and steady-state error analysis in feedback systems.
3. **Root Locus Analysis:** Root locus plots, general rules for constructing the root locus.
4. **Frequency Response Analysis:** (*Project begins and skill evaluation pre-survey*) Bode diagrams, Nyquist plots stability and relative stability analysis, systems with transport lags,

gain and phase margins, closed-loop frequency response, frequency domain performance specifications, peak resonance, resonant frequency, and bandwidth.

5. **Time and frequency domain design of control systems:** PID design, lead-lag compensation.
6. **Analysis and control design in the state space:** State transition matrix, controllability and observability, full-state feedback control design and pole placement, optimal state space control system design, linear quadratic regulator.
7. **Aerospace applications:** Classical and modern control theory: (*Skill Evaluation Post-Survey*)

2.3 Specific Research Objectives

In this study the TRECS (active learning via hardware) treatment was implemented as an optional project assignment which takes about 6 weeks to complete. The specific objectives of this research are to investigate student's conceptual and application-level understanding before and after interacting with the TRECS. It is critical to determine which specific concepts are reinforced and/or developed using active learning facilitated by the TRECS alongside a standard classroom model. Ancillary practical skills are also of interest, such as hardware implementation and makerspace machinery operations, and therefore inquiries to the development of those skills were attempted.

Table 1 - Desired learning outcomes and specific objectives for TRECS implementation.

Objective	Description	Metrics	Expected Course Outcome
Control Theory Knowledge	State-space representation	Knowledge & Understanding	Develop mastery level understanding of analysis of controlled linear SISO systems.
Control Algorithm Knowledge	PID control, optimal control	Knowledge & Understanding	Develop mastery level understanding of design of controlled linear SISO systems.
Makerspace Skills (project only)	Embedded Software	Practical Skills	Write sketches in the Arduino IDE that compile onto the system controller and allow for real-time visualization of sensor data.
Electronics Skills (project only)	Arduino, micro-controllers, dc power supply, electronic speed controller, brushless motor.	Practical Skills	Assemble a robotic device that includes an Arduino nano, electronic speed controller, brushless motor, and rotary position sensor.

2.4 Skill Self-Evaluation Survey

As discussed previously, determining changes in skills and student capabilities is difficult. Assessing changes based on overall course grades provides a very crude measure and almost always introduces biases based on the nature and content of the assessments. Assessments using grades on individual assignments are similarly problematic unless the assessment is carefully designed to measure each learning objective neutrally. This also requires significant time and effort of the specific instructors. We chose an alternative approach to determining the impact of the experiential learning with TRECS.

A skill self-evaluation survey was designed to determine how the TRECS may have developed analytical skills, practical skills, and knowledge & understanding of course material. The skill evaluation was a self-reported survey distributed to all students in the course before and after the TRECS assignment. To control for instructor and course variation, the skill assessment survey was only distributed to the Fall 2020 Control Analysis (AE3531) class. “Users” were the 40 students who voluntarily chose to complete the TRECS assignment, and “Non-users” were the 24 students who chose not to use the TRECS. The pre- and post-surveys were identical, except for

the addition of three questions about the overall experience of using the TRECS sent to Users afterwards. The skill evaluation was divided into four categories: control theory, control algorithms, electronics familiarity, and makerspace skills. The students were asked to rate their skill level with the following prompts:

1. Please indicate your knowledge of the following linear control concepts:
2. Please indicate your knowledge of the following control algorithms:
3. Please indicate your ability for the following maker skills:
4. Please indicate your familiarity with the following electronics tools/components:

The answers to these prompts were presented to the students on a non-numerical Likert scale with choices listed in Table 2. Each topic within the categories was presented individually.

Table 2 - Skill assessment score valuations.

Maker Skills	None/Basic	Amateur	Enthusiast	Proficient	Expert
Electronics	Not familiar	Slightly familiar	Moderately familiar	Very familiar	Extremely familiar
Control Theory	Not knowledgeable	Slightly knowledgeable	Moderately knowledgeable	Very knowledgeable	Extremely knowledgeable
Control Algorithms	Not knowledgeable	Slightly knowledgeable	Moderately knowledgeable	Very knowledgeable	Extremely knowledgeable
Makerspace skills	None/Basic	Amateur	Enthusiast	Proficient	Expert

The survey was distributed to both groups via email. The user group was contacted directly from the contact sheet acquired during the TRECS ordering process, while the Non-users were contacted through the course instructor using an anonymous link. The surveys' response rates are shown below in Table 3.

Table 3 - Response rates for Fall 2020 skill assessment survey.

	Users	Non-users
Before	22.5% (n=9)	50% (n=12)
After	42.5% (n=17)	66.7% (n=16)

The skill survey was distributed on October 12 for Users and October 19 for Non-users, about 8 weeks into the semester. Many of the topics in the control theory section of the skill assessment had already been covered, those of which are listed in the course description. The project had already been distributed and some students had already assembled the device. The project was assigned as an optional assignment and could be used to replace a written exam grade. Both sets of students took the same final exam, homework assignments, and two midterm exams, one of which was completed before the survey. The main goal of the skill assessment is to isolate any skills that were developed while using the TRECS that are not as developed without it.

CHAPTER 3. RESULTS AND DISCUSSION

The skill and knowledge survey results are detailed in the next few sections. These results represent the data accumulated from the Fall 2020 control analysis class. This class was split about 60/40 between Users and Non-users and therefore allowed the opportunity for a direct comparison between the two groups. The data is displayed as diverging stacked bar charts with a baseline of between the lowest reported level and the second lowest level (for each topic.) Hence, the lowest reported level is considered negative while the higher levels are considered positive. The top two bars represent the Nonusers (control group), before and after the course. The bottom two bars represent the Users (treatment group), before and after the course. The numbers of responses are presented as percentages of each sample, $n=12$, 16, 9, and 17 for Nonusers before (N_b), Nonusers after (N_a), Users before (U_b) and Users after (U_a), respectively. Additionally, a one-tailed Mann-Whitney U-test with a 90% confidence interval was employed to test whether each group improved significantly between the two surveys, and whether Users scored higher than Nonusers on the post-survey. The null hypothesis, H_0 , states that for randomly selected values X (before) and Y (after) from two populations, the probability of X being greater than Y is less than or equal to the probability of Y being greater than X . Therefore, rejection of the null hypothesis would state that the probability of Y being greater than X is greater than the converse. In other words, the distribution of responses for the after group, Y , will have increased.

Table 4 - Results of a two-tailed Mann-Whitney U-test comparing Users ($n=9$) and Nonusers ($n=12$) responses to the pre-survey.

	SS	PID	Optimal	MC	Arduino	ESC	Motor	Power	Embedded
<i>p-value</i>	0.918	0.858	0.358	0.900	0.664	0.772	1.000	0.362	0.883
<i>U-value</i>	102.0	100.5	112.5	95.0	91.5	94.5	100.0	86.5	95.5

To ensure that both groups started at the same level, a two-tailed Mann-Whitney U-test was performed on the null hypothesis: for randomly selected values X and Y from two populations, (U_b and N_b), the probability of X being greater than Y is equal to the probability of Y being greater than X . The test failed to reject the null hypothesis for any case, indicating statistical similarity between the groups before the treatment.

3.1 Control Theory Knowledge

State space representation is a topic extensively covered in the prerequisite course, System Dynamics, as well as thoroughly present in the Control Analysis course. Both groups encountered state space representation in the class lectures, homework assignments, and midterm exams. The TRECS does incorporate state-space representation in the optimal control section, providing Users with a practical application of this mathematical topic. Both groups were exposed to the same topic related course material, but Users received additional practice with the topic, specifically in an application-level format on a real physical system. This difference supports the creation of a hypothesis that both groups will improve significantly but that Users will achieve a higher level of significance.

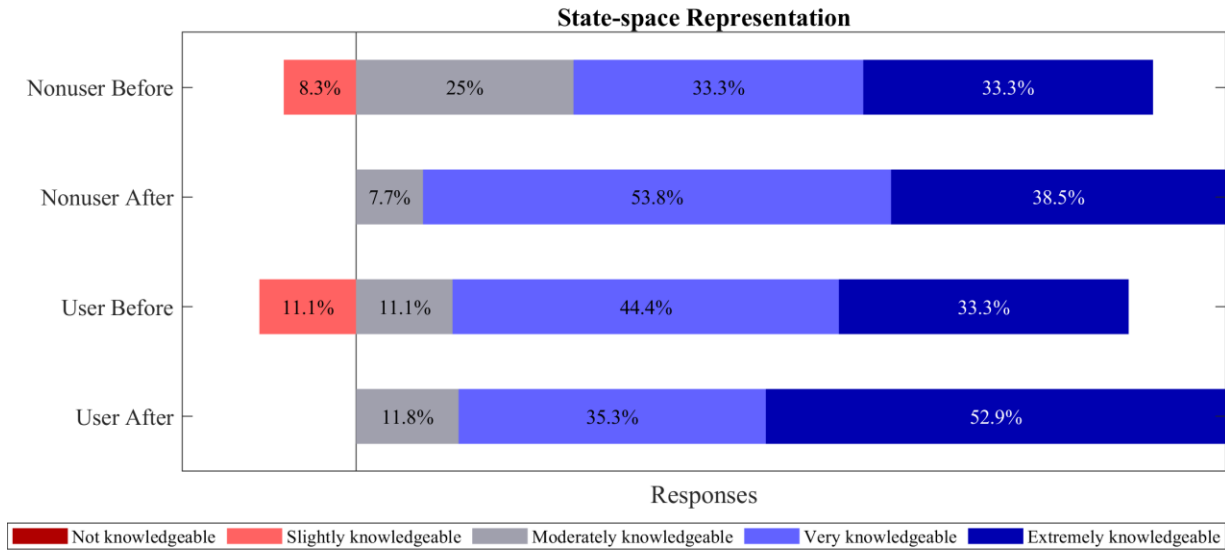


Figure 12 – Knowledge level ratings for state-space representation, Likert response frequency distribution, Fall 2020 Control Analysis course (n=12, 16, 9, 17.)

A more subtle observation on the response distribution is presented here. The largest response expansion for nonusers was in the “very knowledgeable” category, while Users’ largest expansion was in the highest level, “extremely knowledgeable.” Median knowledge levels in groups U_b and U_a were “very knowledgeable” and “extremely knowledgeable,” respectively, however, Users’ response distribution did not increase significantly (p -value = 0.1650.) The complete results of the one-tailed Mann-Whitney tests are found in Table 5.

Table 5 – State space representation Likert response distribution one-tailed Mann-Whitney U-test, $H_0: P(Y>X) \leq P(X>Y)$, Rejecting H_0 indicates that the median of Y is significantly greater than the median of X. 90% confidence interval.

X	Y	n_1	n_2	U	p-value	Reject H_0
N_b	N_a	12	16	139.5	0.2146	No
U_b	U_a	9	17	103.5	0.1650	No
N_a	U_a	16	17	189.5	0.3351	No

3.2 Control Algorithm Knowledge

Control algorithms are at the heart of control system design and analysis. The course covers the topic extensively as students in both groups designed and analyzed control algorithms during written homework problems and written exams. The controller implemented in the TRECS project utilizes a P, PD and PID algorithm. Users experiment with these algorithms by applying them to the system, observing the response behavior, and adjusting the gains to improve performance. Users also get experience with optimal control by utilizing a linear quadratic regulator to find optimal PD and PID gain values. This thesis asserts the hypothesis that due to their applied experience with PID and LQR control algorithms, Users will improve significantly beyond Nonusers on both topics.

3.2.1 *PID Control*

As a part of a separate student perception and feedback survey in Spring 2020, 14 of the 22 TRECS users said that the course concept they understood the most after the project was PID control. The skill evaluation was performed the following semester hoping to verify these findings. The structure of the PID control algorithm had already been covered in the course before the pre-survey was sent out, while the lecture material on the design of PID algorithms and tuning gains for them appeared between the surveys. The entire PID topic was covered again in the midterm and final exams. The User group had the opportunity to connect the theoretical concepts to the physical world by designing, applying, and tuning various PID controllers on the TRECS. Thus, it is expected that both groups will report a significant increase and that Users will be report higher levels than Nonusers.

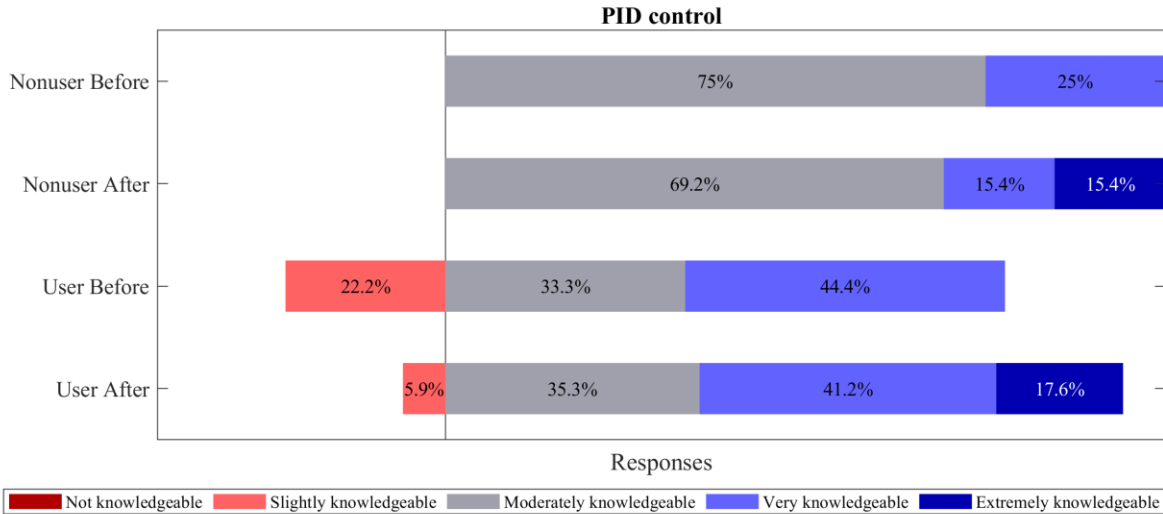


Figure 13– Knowledge level ratings for PID control algorithms, Likert response frequency distribution, Fall 2020 Control Analysis course (n=12, 16, 9, 17.)

Users’ median response increased from “moderately knowledgeable” to “very knowledgeable,” although the response’s distribution failed to increase significantly (p -value=0.1254, See Table 6.) All Nonusers reported being “moderately knowledgeable” or higher for this topic before and after the course, while Users that reported being “slightly knowledgeable” reduced from 22.2% to 5.9%. Additionally, both groups realized increases in “extremely knowledgeable” responses, from 0% to 15.4% and from 0% to 17.6%, for Nonusers and Users, respectively.

Table 6 – PID control algorithm Likert response distribution one-tailed Mann-Whitney U-test, $H_0: P(Y>X) \leq P(X>Y)$, Rejecting H_0 indicates that the response distribution of Y is significantly greater than that of X . 90% confidence interval.

X	Y	n_1	n_2	U	p -value	Reject H_0
N _b	N _a	12	16	148.5	0.3166	No
U _b	U _a	9	17	100.0	0.1254	No
N _a	U _a	16	17	179.5	0.1666	No

3.2.2 Optimal Control

Optimal control had not been covered before the pre-survey was distributed but was covered in the interim between surveys. Optimal control refers to a swath of control algorithms centred around the mathematical concept of optimization that typically involves the minimization of a cost function. In the course, the primary focus is on optimal control algorithms in the state-space, such as the linear quadratic regulator (LQR). While both groups were subjected to the same lectures on this topic, the Users were able to connect the theoretical concepts to the practical application while using the TRECS assignment, which has students design and apply an LQR controller to find optimal gain to improve the performance of a PID controller. It is expected that both groups will report a significant increase and that U_a will report higher levels than N_a .

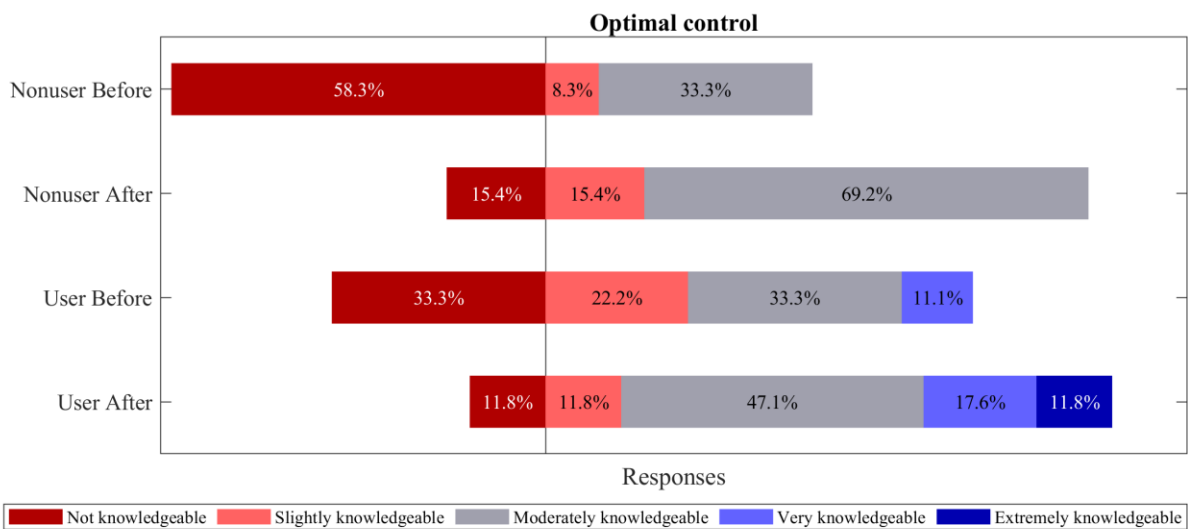


Figure 14– Knowledge level ratings for optimal control algorithms, Likert response frequency distribution, Fall 2020 Control Analysis course (n=12, 16, 9, 17.)

The median response for Nonusers increased from “not knowledgeable” to “moderately knowledgeable” and exhibited a significant response distribution increase (p -value = 0.0292, Table 7.) Users also reported a significant (p -value = 0.0583) increase in response distribution as the median shifted from “slightly knowledgeable” to “moderately knowledgeable.” Additionally, 29.4% of U_a reported being “very knowledgeable” or “extremely knowledgeable,” while none of N_a responded at that level.

In addition, the U_a response distribution was found to be significantly (p -value = 0.0930) higher than N_a . Since both groups exhibited similar response distributions in the pre-survey, it can be concluded that the Users have improved beyond Nonusers regarding optimal control.

Table 7 - Optimal control algorithm Likert response distribution one-tailed Mann-Whitney U-test, $H_0: P(Y>X) \leq P(X>Y)$, Rejecting H_0 indicates that the response distribution of Y is significantly greater than that of X . 90% confidence interval.

X	Y	n_1	n_2	U	p -value	Reject H_0
N_b	N_a	12	16	122.0	0.0292	Yes
U_b	U_a	9	17	91.5	0.0563	Yes
N_a	U_a	16	17	171.0	0.0930	Yes

3.3 Electronics Hardware

There were six electronics topics in this category. One was deemed irrelevant as it referred to a component no longer present on the TRECS device. The following 5 topics cover the extent of the hardware used in the TRECS device. The charts show a distribution of the responses to the Likert scale question; Please indicate your familiarity with the following electronics tools/components. The asserted hypothesis is that Users will report an increased familiarity for the

electronics used in the TRECS. In particular, the Arduino Nano is heavily used as students are required to write firmware and connect it to the rotary position sensor and electronic speed controller. The Arduino is a microcontroller and therefore it is expected that Users will see a significant increase in both categories. As for Nonusers, none of the electronics in this category are covered in the course lecture material. These students did not interact with the hardware and therefore it was proposed that there would be no increase in familiarity for Nonusers on any of the electronics topics.

The common trends in this category are significant (p -value < 0.10) rightward shifts (increased familiarity) for Users' response distribution, although the median values remain constant throughout. In some cases, Nonusers' response distribution appeared to decrease, and hence for those topics the null hypothesis was reversed to become $P(N_a > N_b) \geq P(N_b > N_a)$ and a right tailed Mann-Whitney U-test was performed. In other words, if this right tailed test rejected the null hypothesis, the findings would indicate that Nonusers' familiarity with a topic decreased significantly (p -value < 0.10 .) Despite the median responses decreasing in a few cases, none of the Nonusers' response distribution decreased significantly. This shift could be attributed to statistical noise, a change in the sampled population (see Table 3,) or a Dunning-Kruger effect [42]. Both N_b and U_b medians were found to be "slightly familiar" or in one case "not familiar" (Nonusers, Arduino) with all the hardware. The differences between Users and Nonusers response distribution to the pre-survey was found to be statistically insignificant (see Table 4.)

3.3.1 *Micro-controllers*

The Arduino Nano is a microcontroller that TRECS users utilized during the assignment. Users wrote sketches within the Arduino IDE and then sent them to the microcontroller to be

compiled and ran. Users were also required to attach the microcontroller to a rotary position sensor, power supply, and electronic speed controller via a custom printed circuit board. Despite microcontrollers being common in industry, Nonusers were not exposed to the topic as it is not covered in the course lecture material.

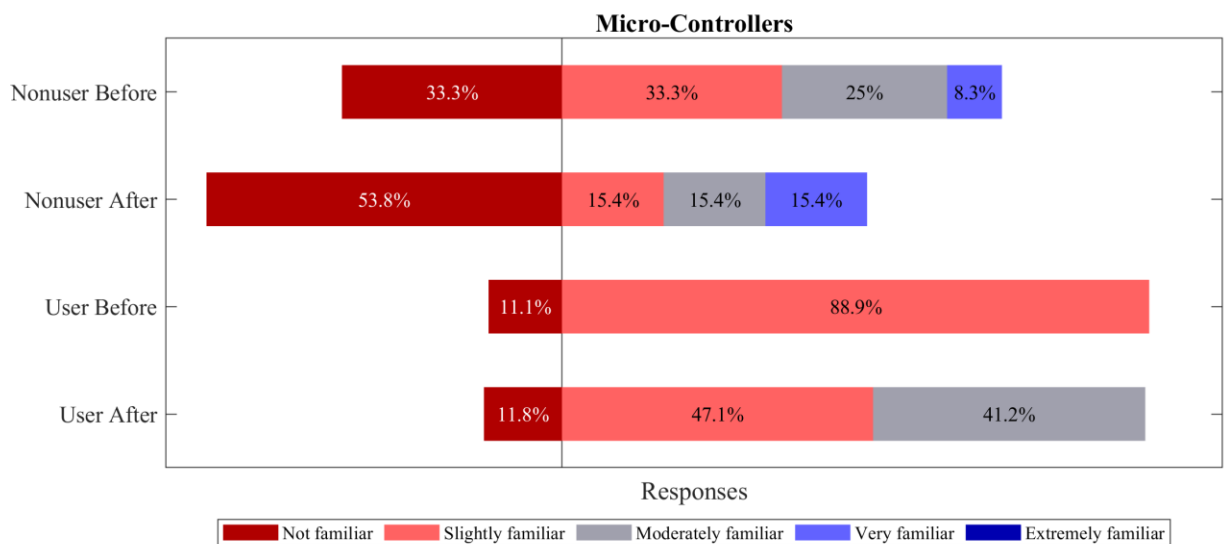


Figure 15 – Familiarity ratings for micro-controllers, Likert response frequency distribution, Fall 2020 Control Analysis course (n=12, 16, 9, 17.)

Despite the median response for Nonusers decreasing from “slightly familiar” before to “not familiar” afterwards, there was no significant decreasing shift in the distribution of responses (see Table 8). Users maintained a median response of “slightly familiar,” however, the distribution increased significantly ($p=0.0357$) with 41.2% responding after the project as “moderately familiar” with micro-controllers.

Table 8 – Micro-controllers Likert response distribution one-tailed Mann-Whitney U-test, $H_0: P(Y>X) \leq P(X>Y)$, Rejecting H_0 indicates that the response distribution of Y is significantly greater than that of X . 90% confidence interval. *Since the Nonuser response distribution appeared to shift left, H_0 was reversed to check for a decrease: $P(Y>X) \geq P(X>Y)$.

X	Y	n_1	n_2	U	p -value	Reject H_0
N _b	N _a	12	16	166.0	0.3075*	No*
U _b	U _a	9	17	94.0	0.0357	Yes
N _a	U _a	16	17	171.0	0.1041	No

3.3.2 Arduino

The Arduino utilized in the TRECS is a robust computer with vast applications and a proven track record as a microcontroller. Users operated the Arduino Nano as a microcontroller to send input responses to the electronic speed controller and receive sensor output from the rotary position sensor. The sketches for the Arduino were written in the Arduino IDE and sent to the processor to be compiled. Users also interacted with additional Arduino software, SerialPlot, used to display live plots of data collected during an experiment. Conversely, Nonusers did not have any learning experiences with the Arduino computer or software as it is not covered in the course content.

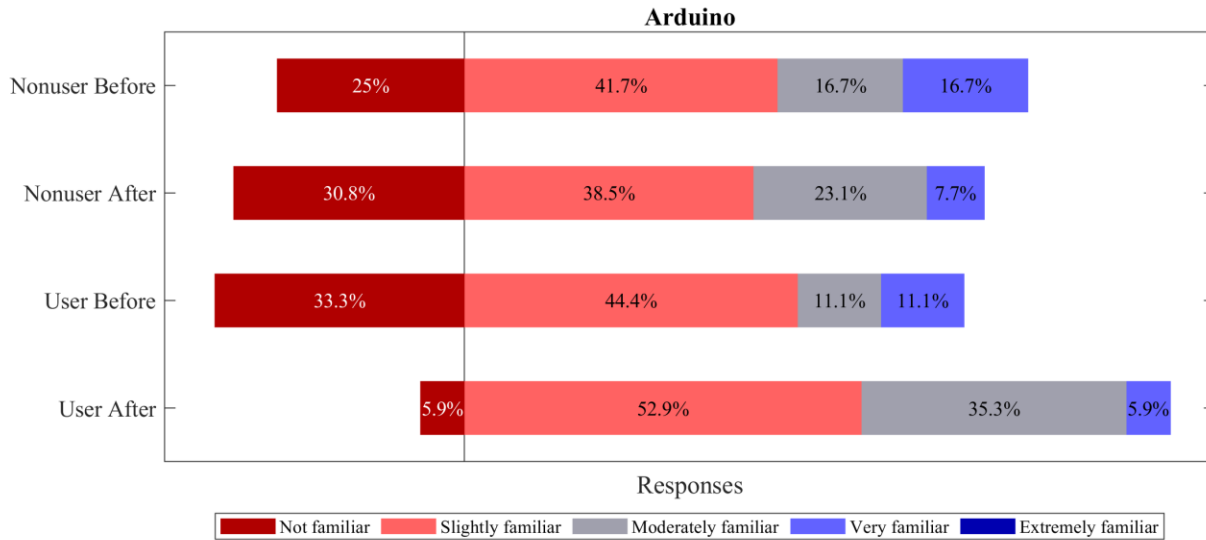


Figure 16 – Familiarity ratings for Arduino, Likert response frequency distribution, Fall 2020 Control Analysis course (n=12, 16, 9, 17.)

The user and nonuser groups rated their familiarities similarly in the pre-survey (see Table 4.) The nonuser’s distribution did not decrease significantly (p -value = 0.3777.) Moreover, Nonusers and Users maintained a median response of “slightly familiar” throughout the course. However, the Users’ reduction of “not familiar” responses from 33.3% to 5.9% significantly (p -value = 0.0903) shifted the distribution rightward (increasing familiarity), which correlates expectedly with the TRECS’ required application of Arduino hardware and software.

Table 9 – Arduino Likert response distribution one-tailed Mann-Whitney U-test, H_0 : $P(Y>X) \leq P(X>Y)$, Rejecting H_0 indicates that the response distribution of Y is significantly greater than that of X . 90% confidence interval. *Since the Nonuser response distribution appeared to shift left, H_0 was reversed to check for a decrease: $P(Y>X) \geq P(X>Y)$.

X	Y	n_1	n_2	U	p -value	Reject H_0
N_b	N_a	12	16	162.5	0.3777*	No*
U_b	U_a	9	17	98.0	0.0903	Yes
N_a	U_a	16	17	176.0	0.1343	No

3.3.3 *Electronic Speed Controllers*

Electronic speed controllers (ESC) are an electronic circuit used to control and regulate the speed of an electric motor. When used to control a brushless DC motor, the ESC inputs a reference speed value from the output of the control algorithm and outputs pulses of current delivered to the several windings of the motor. The timing of these currents, which is controlled by the ESC's firmware algorithms, determines the speed of the motor.

While they appear in the subsequent control laboratory course, electronic speed controllers are not a topic covered in the Control Analysis course. Therefore, Nonusers were not subjected to any learning experiences with ESCs. Application of the ESC in the TRECS is mostly plug-and-play, such that Users must connect their ESC to the Arduino via a PCB. Once connected, Users compile a provided ESC test sketch to calibrate the ESC. Consequently, it is expected that Users will report a significant increase in familiarity while Nonusers will report no change.

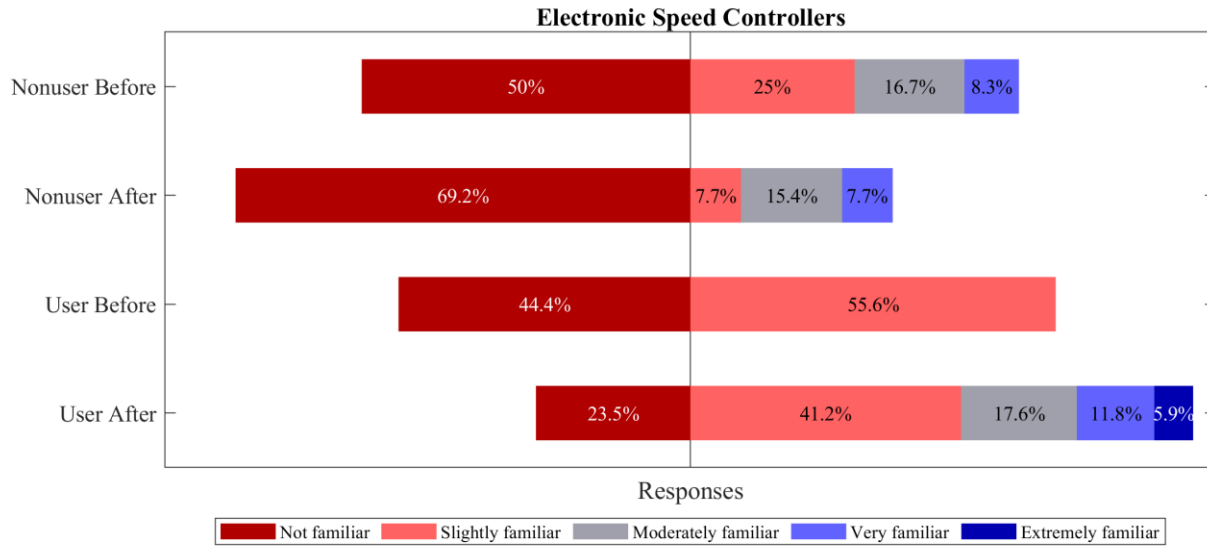


Figure 17 – Familiarity ratings for electronic speed controllers, Likert response frequency distribution, Fall 2020 Control Analysis course (n=12, 16, 9, 17.)

Although the Nonusers’ median response dropped from between “slightly familiar” and “not familiar” to “not familiar” and it appears that the response distribution shifts leftward (decreasing familiarity), the decreasing shift was found to be statistically insignificant. On the other hand, Users’ response distribution increased significantly (p -value = 0.0538) despite a constant median value and it was found that U_a reported significantly (p -value = 0.0269) higher familiarity than N_a . This topic and optimal control are the only topics for which Users have improved significantly beyond Nonusers over the course of the surveys.

Table 10 – ESC Likert response distribution one-tailed Mann-Whitney U-test, $H_0: P(Y>X) \leq P(X>Y)$, Rejecting H_0 indicates that the response distribution of Y is significantly greater than that of X . 90% confidence interval. *Since the Nonuser response distribution appeared to shift left, H_0 was reversed to check for a decrease: $P(Y>X) \geq P(X>Y)$.

X	Y	n_1	n_2	U	p -value	Reject H_0
N _b	N _a	12	16	168.0	0.2592*	No*
U _b	U _a	9	17	90.5	0.0536	Yes
N _a	U _a	16	17	156.5	0.0269	Yes

3.3.4 Brushless DC Motors

Brushless DC motors are extensively utilized in electronics across all engineering disciplines. Their low power demand and size variations contribute to these motors being versatile components. The TRECS project utilizes a brushless DC motor, while the course does not cover the topic. The use of the motor in the project is plug-and-play, except for assembly, where Users must attach the propeller to the base of the motor. The students do not send control signals directly to the motor, and therefore did not have to learn the intricacies of the stator design. Instead, the control signals determined by the Users are sent to the ESC, which modulates the signal to control the speed of the motor.

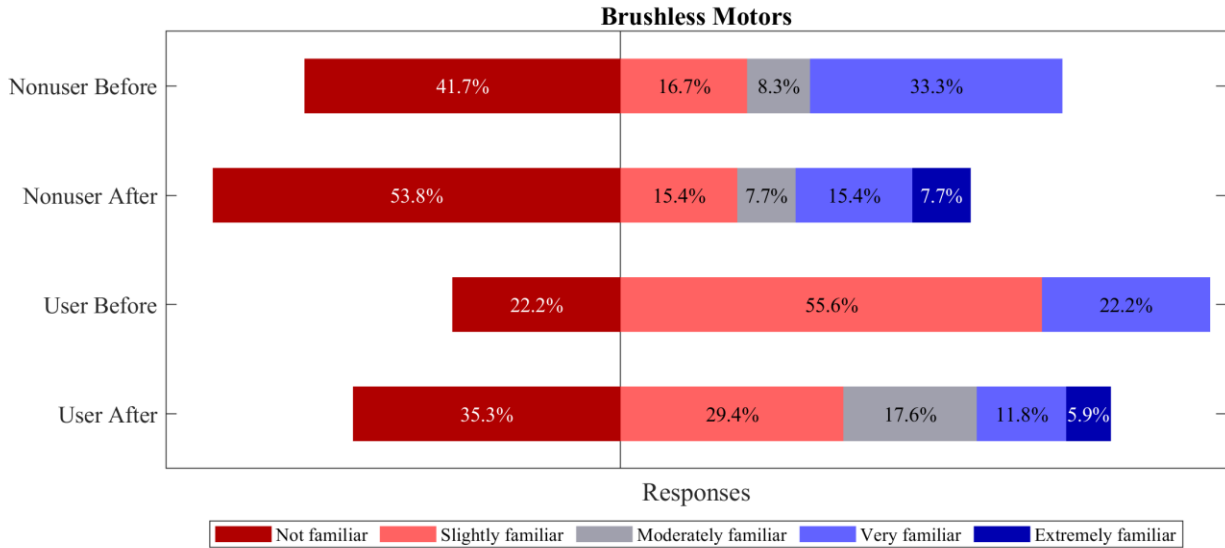


Figure 18 – Familiarity ratings for brushless motors, Likert response frequency distribution, Fall 2020 Control Analysis course (n=12, 16, 9, 17.)

Despite N_b reporting a large percentage of “very familiar” responses with these motors compared to the other electronic components, no significant ($p\text{-value} < 0.10$) change in the distribution occurred. Although both User and Nonuser groups seem to exhibit a decreasing distribution, neither shift was found to be significant (see Table 11.) It can be concluded that Users did not have sufficient learning experiences with brushless DC motors to affect a familiarity increase.

Table 11 – Brushless DC motors Likert response distribution one-tailed Mann-Whitney U-test, $H_0: P(Y>X) \leq P(X>Y)$, Rejecting H_0 indicates that the response distribution of Y is significantly greater than that of X. 90% confidence interval. *Since User and Nonuser response distributions appeared to shift left, H_0 was reversed to check for a decrease: $P(Y>X) \geq P(X>Y)$.

<i>X</i>	<i>Y</i>	<i>n</i> ₁	<i>n</i> ₂	<i>U</i>	<i>p</i> -value	Reject <i>H</i> ₀
N_b	N_a	12	16	165.0	0.3137*	No*
U_b	U_a	9	17	123.5	0.4726*	No*
N_a	U_a	16	17	188.0	0.2827	No

3.3.5 DC Power Supplies

The control analysis course does not cover the topic of DC power supplies. The TRECS project utilizes a DC power supply but only as a plug-and-play component. It is expected that neither group will experience a significant increase in familiarity on this topic.

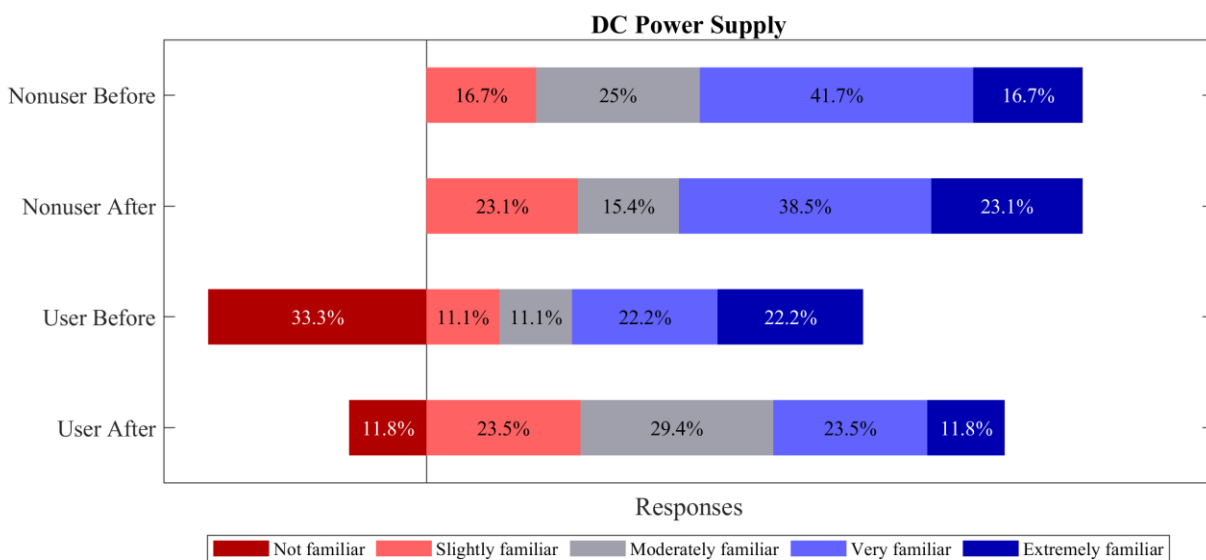


Figure 19 – Familiarity ratings for DC power supplies, Likert response frequency distribution, Fall 2020 Control Analysis course (n=12, 16, 9, 17.)

Response distribution for Nonusers failed to reject the null hypothesis, maintaining relative consistency throughout the course, with a median pre- and post-survey median response of “very familiar.” Students from both groups are more familiar with the power supply compared to other hardware components. The Users appear to begin at a deficit in this category, but no significant response distribution difference was found between U_b and N_b (see Table 4.) DC power supplies

are covered thoroughly in the electronics & circuits course, a mandatory course for aerospace students, but whether these students had previously taken that course was undetermined.

Table 12 – DC power supply Likert response distribution one-tailed Mann-Whitney U-test, $H_0: P(Y>X) \leq P(X>Y)$, Rejecting H_0 indicates that the response distribution of Y is significantly greater than that of X . 90% confidence interval.

X	Y	n_1	n_2	U	p -value	Reject H_0
N_b	N_a	12	16	153.5	0.4743	No
U_b	U_a	9	17	118.5	0.4728	No
N_a	U_a	16	17	233.0	0.9204	No

3.4 Maker skills

There was a total of four makerspace topics on the skill evaluation. Three were deemed irrelevant as neither the class nor the TRECS project used for this course demanded the use of laser cutting, 3d printing, or soldering. For now, the only relevant maker skill is embedded software.

3.4.1 Embedded Software

Embedded software, or firmware, is a broad term that refers to specialized programming within non-PC devices used to control functions of a device. In this case, students write sketches in the Arduino IDE that once completed can be compiled onto the microchip inside the Arduino. Once the sketch is compiled, it is detached from the student's PC and begins to run on the Arduino independently. The interface provided by Arduino is clean and intuitive, which is not the norm for firmware applications. The topic of embedded software is not covered in the control analysis lecture material.

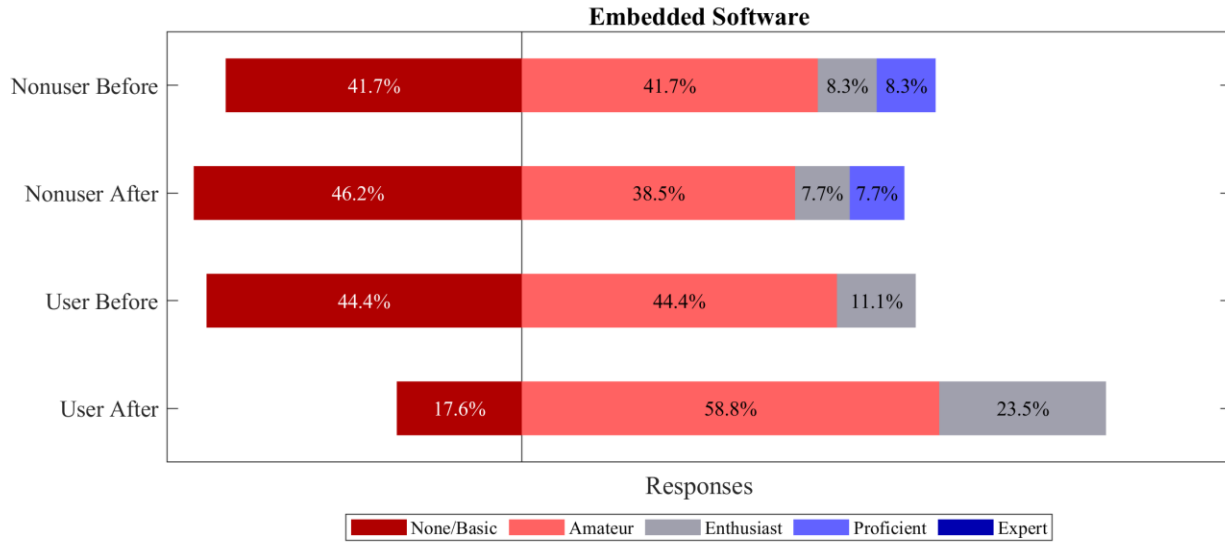


Figure 20 – Embedded software skill level Likert response frequency distribution for Fall 2020 control analysis students. (n=12, 16, 9, 17)

Users' response distribution was found to miss the 90% confidence interval for significant increase with a p -value of 0.1058. The null hypothesis could not be rejected for any of the comparisons of response distributions. Although, the percentage of Users who responded with "none/basic" dropped from 44.4% to 17.6% while the percentage who responded with "enthusiast" increased from 11.1% to 23.5%.

Table 13 – Embedded software Likert response distribution one-tailed Mann-Whitney U-test, $H_0: P(Y>X) \leq P(X>Y)$, Rejecting H_0 indicates that the response distribution of Y is significantly greater than that of X . 90% confidence interval.

X	Y	n_1	n_2	U	p -value	Reject H_0
N_b	N_a	12	16	166.0	0.6257	No
U_b	U_a	9	17	94.0	0.1058	No
N_a	U_a	16	17	171.0	0.1152	No

CHAPTER 4. CONCLUSIONS

4.1 Summary of Thesis Objectives and Goals

The objectives of this thesis were two-fold: to ascertain the effect of the TRECS on course topic familiarity and knowledge development and to propose an improved mixed methods study for evaluation of educational robotics learning experiences. This study utilizes the findings of a pre- and post-treatment skill evaluation self-assessment survey. The study took place over the course of an undergraduate aerospace engineering control analysis course at Georgia Institute of Technology. The class was separated into two groups, Users (treatment group) and Nonusers (control group.) The applied treatment was a six-week project utilizing the Transportable Rotorcraft Electronic Control System which provided hands-on learning experience with electronics and control theory topics.

The pre- and post-surveys were distributed to both groups of students to evaluate differences in knowledge of control theory and algorithms, familiarity with electronic components and maker skill levels. The study aimed to determine if utilizing the TRECS project alongside the course lecture material would affect learning outcomes. The topics covered by the TRECS align with the course objectives of mastery of analysis and design of controlled linear SISO.

The other goal of this study is to assess the limitations of the current assessment methodology and propose an alternative study that would more accurately gauge the effect of the TRECS. Considerations of poor metric design, response biases and lack of randomization have been made. Recommendations were focused on improving the study's trustworthiness, verification, and

transferability to other hands-on learning devices by employing a mixed method approach of quantitative and qualitative measures.

4.2 Major Conclusions

This study contributes to a long line of similar take-home laboratory experiments and robotics projects and aims to address a call for increased practical skill development in engineering education. The TRECS projects' utilization of common electronics hardware and control algorithm development makes it relevant to industry standards and academic learning outcomes. The pre-survey results showed that Users and Nonusers rated their knowledge and familiarity of the topics similarly before the treatment.

The survey asked about control theory and algorithms, which Users reported to have significant ($p\text{-value} < 0.10$) increases in knowledge level for optimal control algorithms. These topics are covered in the course lecture content, homework assignments, and written exams. Although it was found that Users (U_a) reported significantly ($p\text{-value} < 0.10$) higher knowledge level of optimal control algorithms after the course when compared with Nonusers (N_a .) This thesis posits that the hands-on learning experiences and direct application of a linear quadratic regulator optimal control algorithm onto the TRECS helped synthesize the theory with the application and increase the level of knowledge for Users.

The topics of state-space representation, PID control, brushless DC motors, DC power supplies, and embedded software, for both Users and Nonusers, failed to reject the null hypothesis while employing a 90% confidence interval. The null hypothesis, H_0 , states that for randomly selected values X (before) and Y (after) from two populations, the probability of X being greater than Y is less than or equal to the probability of Y being greater than X . Therefore, rejection of the

null hypothesis would state that the probability of Y being greater than X is greater than the converse. In other words, for either group the study failed to show significant increases in knowledge or familiarity for any of the remaining skills. This was found even though state-space and PID control were covered extensively in the course material and applied in the TRECS assignment.

Electronics topics for which familiarity did significantly (p -value < 0.10) increase for Users were micro-controllers, Arduino, and electronic speed controllers. These students interacted directly with these pieces of hardware, leading to this obvious observation. The course lecture material did not cover these electronics and therefore there no comparison can be made between the learning outcomes of lectures with or without the TRECS implementation. This leads to the conclusion that this study is unable to determine the value of the TRECS to foster a learning experience with these electronics or to ascertain the efficacy of the TRECS in comparison to classical lecture methods.

4.3 Limitations

There are many considerations to be made that may have influenced the results of these studies. The project was not randomly assigned, therefore students with higher curriculum engagement and stronger overall academic performance might have been more likely to volunteering for the project. Students with a lesser course load may have felt more comfortable taking on the extra workload. Students may have wanted the option to replace a midterm grade with the project, which has an impact on final grading distributions. The TRECS was also purchased at a cost to the student, which may bias the results between Users and nonusers. Students who could afford to purchase the TRECS could possibly come from higher socio-economic

backgrounds, which has been found to correlate positively with improved academic performance [43]. The validity of these scenarios must be considered in greater detail in future studies of this kind.

The user and non-user groups differ slightly between pre and post surveys. Due to confidentiality constraints, the non-user group remained entirely anonymous. It is therefore possible that the two non-user groups contained different students; we can truly be certain of a 16% congruency. For the user group, the identities of the students were disclosed, due to their participation in the third party supplied project. 89% of U_b are accounted for in U_a but U_a also includes eight students that did not respond to the pre-survey. Additionally, this study is affected by small sample sizes. The skill evaluation response rate was low, particularly for U_b which received only 9 responses for a population of 40.

The nature of the survey and the question design must be considered with the results, such that the skill evaluation was not a direct evaluation, but rather a self-assessment. Therefore, it is reasonable to ingest this information as a measure of confidence or familiarity with concepts/components and not as certifiable skills. It is also important to consider the bias in self-reported data. Self-reports have been found to be particularly accurate on the topic of academic achievements, but when students do misreport, they tend to overreport [44, 45]. The survey is also limited by its focus on course specific development of subject-related knowledge. As for the subject matter of the assessment, the study failed to address a few of the topics covered by the TRECS project, including system identification and dynamical simulation.

Also, consider that Non-users received the survey request from the professor, while Users received it directly from the graduate researcher. The difference in academic authority between

these two distribution channels may have led to additional bias in the dataset. The also study failed to inquire about other qualitative data, such as demographics and setting, that provide a rich description of the sampled participants and a clearer interpretation of the findings. Additionally, the study did not address higher-level, more general learning outcomes such as problem-solving skills, analytical skills, or social and scientific communication.

4.4 Future Work

If the opportunity to continue this research is undertaken, these are some approaches to deal with the limitations of this study. In a holistic mixed-methods study that considers rigor and trustworthiness, there is a balance to be struck between quantitative results and qualitative findings [46, 47]. First, a quantitative metric is considered. The TRECS project is a demanding experience which requires a large time commitment; many engineering students do not have extra time to spend. Offering the TRECS as a midterm grade replacement was the primary motivating mechanism for students to complete it. Unfortunately, incorporating the TRECS into the grading scheme of a course compromises the most common quantitative result, the final course grade. Instead, a proper expansion of this study would include a two-fold test, a hands-on evaluation to measure skill development and a written exam to measure conceptual understanding. To motivate students to complete these assessments, they could be incorporated into the grading scheme as bonus points or regular assignments. Assessments from all variations of the implementation of the TRECS must be graded independently by researchers according to a predetermined metric. Distributing the assessments before students engage with the TRECS and then again after students have completed the TRECS project would be an ideal delivery.

The written assessment would be a typical problem set, from the likes of Ogata [48, 49], curated to probe conceptual level understanding of topics covered by the TRECS. The new study must be sure to evaluate the concepts that were left out of this study, including dynamic modeling, simulation of trajectories, and estimation of parameters. The practical assessment is more cumbersome but allows for the evaluation of the development of application-level understanding. There are numerous examples of hands-on engineering lab kits available that could be used to assess practical skills [30-33, 50-53]. Students could be presented with a hands-on robotics project, like the TRECS, in the form of a box of components, an assembly instruction manual, and a series of tasks to complete. The non-user group could use the TRECS itself as the assessment project. A few tasks such as implementing a PID controller or achieving an optimal trajectory would allow researchers to compare the performances of students' solution to the problem.

Next, qualitative data is considered more trustworthy when it is triangulated from multiple sources. The current study only provides one method of data collection; therefore, an expansion of this study would include additional metrics. As this proposed study reaches interdepartmentally and across multiple institutions and possibly multiple years, a rich and thick description of the participants perspectives and settings will allow readers to make better decisions regarding transferability. These descriptions can be collected from a large sample of the population through a pre- and post-survey. The survey must include inquiries about students' demographic information, setting, other enrolled courses, extracurriculars, and previous experience with hardware or related topics. There are various tools developed for qualitative assessment of project efficacy such as KIPPAS [22] or MSLQ [39] that could be used to supplement this survey. This survey must be designed to describe participants in-depth as to provide a dense sample description and further increase trustworthiness.

The skill survey itself could improve. It would benefit from iterative questioning, such that there are multiple inquiries for each topic, written in various styles to parse out interpretation bias. These changes would vastly improve the assessment of skill development due to the TRECS. Verification of the skills survey is achieved by aligning the written exam and hands-on project skills assessments. It is critical to include the remainder of the skills covered in the TRECS project that were not asked about in this preliminary study. Additionally, a few control questions about topics not related to the TRECS but included in the course, as well as topics neither related to the TRECS or the course could be implemented to serve as additional verification of the results and reveal hidden bias present in the collection method. The survey should again be sent before starting and after completing the TRECS assignment.

An additional layer of qualitative data could be collected from focus groups or interviews. The sample size of the interviewed population would be smaller, as it is a laborious task. Semi-structured interviews would allow for unique case orientation, such that learning more about certain participants could provide further insights into the efficacy of the project. Questions about other Interviews would also provide an opportunity to ask participants if the findings of their survey responses aligned with their perspective. This form of member checking the findings could augment credibility.

The scale of the study must also be increased. While one class' population is only 60 students, a larger study could take place in a massive open online course or over multiple semesters. Extending the study over multiple semesters would allow for additional consideration of teaching styles of different professors. Moreover, there are multiple control analysis courses available at Georgia Tech such as the mechanical engineering and electrical engineering versions. Incorporating the TRECS across departments will help control for hidden bias. Better yet, tracking

TRECS users at another university, such as at Worcester Polytechnic where the TRECS has been implemented a couple of times already, would further reduce sampling bias. Of course, the students should be selected randomly, rather than rely on volunteers. Random sampling of students will prevent many selection biases such as student strength and course load, which is information that will be collected as well.

Thus, limitations of this study include small sample size, sole focus on assessment of course specific skill development and subject related knowledge, poor metric design causing sampling and selection bias, and self-reported data. This study relies exclusively on one dataset and therefore verification of these findings is necessary and would require triangulated datasets such as a written knowledge test or interviews with students. Improvements to the study have been put forth to determine how a holistic mixed-methods approach would more accurately gauge the effectiveness of the TRECS and determine transferability of the findings through increased trustworthiness implementations. The main recommendation of this study is for future researchers to continue to develop better instrumentation for studying hands-on learning experiences at the undergraduate level. This thesis cannot conclusively recommend the implementation of the TRECS device in additional classes without further investigation into its efficacy.

APPENDIX

TRECS Final Report Grading Rubric

- Formatting (5 pts)
- Introduction (10 pts)
 - Include the objective of the project itself (2 pts)
 - Describe how the system was built and the software tools used to simulate and analyze the system (4 pts)
 - Briefly mention the main results and findings of the overall project (4 pts)
- Physical Device and Testing (10 pts)
 - Evidence of functional device and completed device tests (4 pts)
 - Plot of device response to default gains (4 pts)
 - Answer to question (2 pts) - Using the **default PID controller gains**, plot the device's response to a step input of 0° along with the drive signal on the same figure. What do you observe about the response and how might it be improved?
- Dynamics Modeling (10 pts)
 - Derivation of equation of motion for modeling the system (8 pts)
 - Simplification of model (2 pts)
- Model Approximation (15 pts)
 - Procedure and results for determination of each term's coefficient (10 pts)
 - Table of final coefficient values and the final equation of motion (5 pts)
- P Controller (10 pts)
 - Plots for 3 different gains tested (5 pts)

- Answer to Question 2.3.1.(e) (2.5 pts) - Was the system able to reach the desired signal in any of the three tests, why or why not?
- Answer to Question 2.3.1.(f) (2.5 pts) - What, if any, differences are there between the simulated response and the actual response? What factors may have caused this?
- PD Controller (10 pts)
 - Plots of 3 different gain sets tested (5 pts)
 - Answer to Question 2.3.2.(e) (2.5 pts) - Was the system able to reach the desired signal in any of the three tests, why or why not?
 - Answer to Question 2.3.2.(f) (2.5 pts) - What do you observe about the transient response? (That is, the portion between rest and stabilization.)
- PID Controller (10 pts)
 - Plots of 3 different gain sets tested (5 pts)
 - Answer to Question 2.3.3.(e) (2.5 pts) - Was the system able to reach the desired signal in any of the three tests, why or why not?
 - Answer to Question 2.3.3.(f) (2.5 pts) - Were you able to produce a set of gains that resulted in a response with minimal overshoot, quick rise time, quick settling time, and low steady state error? Why or why not?
- Step Change Test (5 pts)
 - Plot of the actual device response (2.5 pts)
 - Answer to Question 2.3.4.(b) (2.5 pts) - How is this response different from that of the previous section? Why is it different?
- Optimal Control using LQR (10 pts)
 - Derivation of the PD state space model including A and B matrices (2 pts)

- Chosen Q and R matrices, optimal PD gains, and plot of the response (2 pts)
- Answer to Question 2.4.1 (c) (1 pt.) - Using those gains, plot the simulated and actual response to a commanded input of 0° . How did this controller compare to the gains you tested earlier?
- Derivation of the PID state space model including A and B matrices (2 pts)
- Chosen Q and R matrices, optimal PID gains, and plot of the response (2 pts)
- Answer to Question 2.4.2(c) (1 pt.) - Using those gains, plot the simulated and actual response to a commanded input of 0° . How did this controller compare to the gains you tested earlier? Were you able to safely test the device using the computed PID gains?
- Conclusion (5 pts)
 - Explains your overall findings and the importance of the project. (5 pts)

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